THE EFFICIENT MARKET HYPOTHESIS AND GAMBLING ON NATIONAL FOOTBALL LEAGUE GAMES

BY

YOON TAE SUNG

THESIS

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Master's Committee:

Assistant Professor Scott A. Tainsky, Chair
Assistant Professor Carla A. Costa

ABSTRACT

The efficient market hypothesis (EMH) for sport betting states that all publicly available information should be mirrored in betting lines, so there should be no bias of betting outcomes. Because of several similarities to financial markets, the sport betting market is thought of as a fair market. This investigation tests the EMH in the National Football League betting market from the 2002 to 2009 seasons. This study also examines whether there is a bias after a bye week in terms of the EMH. For this investigation we utilized a significance test for proportion and logistic regression. The findings suggest that, among other biases, favorites and favorites on the road won statistically more bets than their opponents after their bye week. This study provides relevant evidence of inefficiencies within NFL betting.

I would like to dedicate this thesis to my family who have made it possible for me to be here today. Without them, this would not be possible.

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CHAPTER 1

INTRODUCTION

Sport Industry

The sport industry represents a large, multi-faceted segment of business as it has a relationship with diverse kinds of industries, such as sports entertainment, sports products and sports support organizations (Williams, 2006) through professional and amateur sports leagues, or recreational sports. Some might think that the sport industry is not as large of an industry when they see and compare its total revenue with other industries (Fort, 2006, p. 2). However, because of the symbiotic relationship with other industries, the sport industry has more power and a bigger effect than its stated economic value. Thus, it is apparent that the importance of the sport industry cannot be measured by its metrics like total revenue.

Humphreys and Ruseski (2008) categorized components of the sport industry: participation sports activities, attendance of sporting events and the viewing sporting events via media. The authors evaluate the business of sports at more than $170 B. This value comes from revenues earned by sports business companies and consumption of goods by recreational participants and spectators. However, if we add other intangible effects of sports, such as image enhancements for countries or companies, the impact would be bigger than the estimate that they provide.

The National Football League

The most popular professional sport league and the largest business of sports in the United States (US) is the National Football League (NFL). Borghesi (2007) noted that of the sports industry's total output, $152B, is 2% of US GDP. The NFL is valued at around $17 B. Its large revenue comes from TV contracts and TV commercials (Fatsis & Pope, 1998), although it has fewer regular season games compared to other sports leagues such as Major League Baseball (MLB) and the National Basketball Association (NBA).

For its history, the professional football league was founded in 1920 with 11 teams as the American Professional Football Association (www.cbssports.com/nfl/history). Two years after its beginning, the league changed its name to the NFL. There was another professional football league, the American Football League (AFL) which formed in 1960 as a rival league, but it merged with the NFL after 1970. Today, the league has 32 teams and the two conferences, the National Football Conference (NFC) and the American Football Conference (AFC), have the same number of teams. Each team plays 16 games per season over 17 weeks with one bye week.

Sport betting market and NFL betting

Sport betting is very popular in the US and it accounts for one ninth of all gambling (Frey & Eitzen, 1991). Betting takes place on horseracing, baseball, football and others. The sport betting market uses several kinds of odds systems. Horseracing betting has representatively employed the pari-mutuel odds system, which payoffs are determined at the end of the races based on wagering volume (Snyder, 1978). However, some other sports betting markets, such as NFL and NBA, have employed the fixed odds system, which was invented in the 1940s and payoffs are clearly announced whenever bettors bet.

As mentioned, the NFL is the most popular and profitable sports league in the US (Borghesi, 2007). This popularity would lead businesses related to the NFL to gain greater revenue than other businesses related to other sports league because of greater symbiotic effects. Thus, the sport betting market can be thought of as one segment of the sports industry in that the popularity of sports league could affect bettors' behavior and the league and the market could benefit from each other.

In the betting market, an enormous amount of money is annually wagered in Nevada, the only state where sport betting is allowed (Summers, 2008). Also, as the most popular annual sporting event, the Super Bowl draws a very large amount of wagers or betting money because of uninformed bettors' interest (Dare & Macdonald, 1996). There are many recreational bettors who just wager on the game for enjoyment as well as informed bettors. Like professional football's popularity in the US, NFL betting is also the most popular among sport gamblers in terms of the amount of wagers (the Center of Gaming Research at UNLV, 2009). In general, 40% of total bets are for the NFL, averaging around $1B per year, followed by basketball and baseball. According to reports from the University of Nevada Las Vegas (UNLV), the annual statewide total wagers on sporting events has been at around $2.4B per year for past 5 years. This figure is only for betting within the State of Nevada. When we count online betting money, the amount of wagers would be much higher. The Entertainment and Sports Programming Network (ESPN) suggested that the amount of money wagered annually in the online sports betting industry is around $63B worldwide (Martin, n.d.). Thus, it is apparent that no one can doubt that the sports betting market is big business.

For the betting odds system, the main reason for the invention of the fix odds system was that the pari-mutuel odds system was somewhat disadvantageous to the bookmaker (Martin, n.d.). Typically, the bettor should pay more commission for the bookmaker when they bet on a favorite rather than an underdog due to its higher winning probability in the pari-mutuel system. If a large underdog, which has a very low probability of winning, wins the bet and a majority of bettors wager on the large underdog, the bookmaker would lose a lot and finally go into the red since payoffs are larger than when a favorite wins the bet. However, one of the fixed odds system, which means that the commission is fixed at a certain percentage (Borghesi, 2003), the NFL point spread betting employs 11/10 rule for the commission, which is called "vigorish" or "juice" (Vergin & Scriabin, 1978). In brief, the rule means that bettors need to wager $110 per bet to earn $100. Hence, $10 is the commission for the bookmaker and all bettors should pay the same commission regardless of which team they wager on. Moreover, because of this rule, the bookmaker is guaranteed 4.54% of profit no matter which team wins the bet, under the assumption that money wagered on each team is balanced (Gray & Gray, 1997). For instance, if one bettor bets $110 on each team, the total money that bookmaker receives is $220. After one team wins the bet, the bookmaker only pays out $210 to the winner and earns $10. Thus, of $220, it always makes $10 (10/220 = 0.0454).

For the NFL point spread betting, every bettor pays the same amount of commission regardless of favorites or underdogs (Woodland & Woodland, 2000) whereas for MLB betting, the bettors pay different amount of the commission depending on the favorites or the underdogs. For instance, if the New York Yankees (NYY) plays the Chicago Cubs (CHC) and the odds prices are -$180 for NYY and $130 for CHC, bettors must bet $180 on NYY to earn $100 or $100 on CHC to earn $130. Thus, a bettor in MLB has a greater risk than a bettor who wagered on CHC because of the different amount of wagering. The higher probability of winning, the more commission a bettor must pay. Unlike MLB bets, people do not need to care about the eventual winner of the games in point spread and over-and-under (O/U) betting. With O/U, bettors bet whether the total score of both teams will surpass a given total. For point spreads, winning the bet is only determined by the difference of scores between two teams regardless of which team wins the game. For example, the New England Patriots (NE) play the Green Bay Packers (GB) and the sports bookmaker announces the point spreads, -4 for NE and +4 for GB. In this case, NE is the favorite and GB is the underdog. If NE wins the game by 5 or more points, bettors for NE win: if GB loses by 3 points or fewer or wins outright, then bettors who bet on GB win. Therefore, the difference of score is the only determinant of winning the bet in the NFL betting.

Market Efficiency

Researchers in finance and economics have tried to test the efficiency of a financial market, such as the stock market. Stock markets are generally understood to be fair and efficient. Testing market efficiency is based on the efficient market hypothesis (EMH), which means that the market fully reflects all available information into stock prices (Malkiel, 2003). Although there is new information that can affect the stock prices, it should be mirrored into stock prices as well in order for the market to offer fair information to investors. In this manner, no one can predict future prices. This means that if a market is efficient, no one can make a profit based on any information (Timmermann & Granger, 2004). If biased outcomes are noticed, it would give people a chance to predict the future prices or outcomes and they would finally make a positive return.

These days economists have expanded their testing market efficiency in the sports betting market. The main reason is that there are several similarities between the two markets as well as unique characteristics of the betting market. That is, there are uniquely a lot of investors (bettors), they sell or buy their assets (betting), there are large sums of money involved, and there are commissions or transaction fees (for bookmakers in the betting market or specialists in stock market) (Amoako-Adu et al., 1985). Also, like investors in the stock market, it is easy for bettors to gather information, such as game statistics, to make a decision on gambling. The unique difference between the two markets is that the future outcome is clear in sports games. Stock prices do not have an accurate ending point while sports games have clear ending points and outcomes (Woodland and Woodland, 1994). Thus, it is hard to investigate future outcomes and market efficiency in the stock market. Therefore, the sports betting market is a possible alternative to the financial market for studying market efficiency by comparing actual outcomes with the expected outcomes provided by the bookmaker.

Studies investigating the EMH of the sport betting market also assume that the bettor cannot make a profit on average by obtaining outside information (Osborne, 2001); there should not be any winning or profitable strategies on gambling, and all relevant information should be reflected in betting lines. Therefore, the main objective of this study is to investigate the NFL betting market, under the assumptions of the EMH, and to study whether or not there are certain strategies that lead the bettor to beat the market and be profitable on average.

CHAPTER 2

LITERATURE REVIEW

Market efficiency

The idea of testing market efficiency in sports betting is derived from the traditional financial market. How financial markets are tested and interpreted in terms of the EMH is critical since the same situation and assumptions are applied to testing market efficiency in the sport betting market.

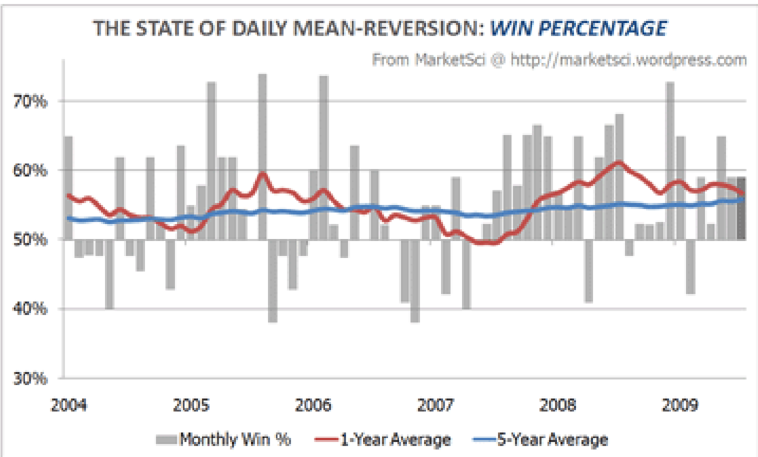
In regards to the stock market, Malkiel (2003) explained that the idea of the "random walk" is employed in EMH and, in an efficient market, no one can make abnormal returns. He stated:

> The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, then tomorrow's price change will reflect only tomorrow's news…resulting price changes must be unpredictable and random. As a result, prices fully reflect all known information, and even uninformed investors buying a diversified portfolio at the tableau of prices given by the market will obtain a rate of return as generous as that achieved by the experts
> (p. 59).

By his definition, it is very difficult to make a positive return on average whoever buy or sell their assets. If people make their own portfolio based on past price change and recent news, that information would not give certain advantages to investors since all publicly available information is included in stock prices. He also stressed that only current information, especially from that day, is reflected in the day's prices. Some people might think that they can beat the market and take positive returns from their action based on their own information. However, Daniel et al. (1998) mentioned that if people think this way, it is apparent that they are misunderstood the concept of an efficient market; they are overconfident to their subjective information and ignoring public information offered from the finance market when people buy or sell their assets. Consequently, it is very hard for informed or uninformed investors or even experts to predict future prices when they invest their money in certain stocks.

Also, even if investors find certain tendencies in the stock market and then use this information for investing, it would not be profitable due to mean reversion (Fama & French, 1988). Sometimes we see a significant increase on a company's value over a short-term period and some people might believe that this is going to continue for a long time. However, the stock market tends to keep its average in terms of stock prices (Malkiel, 2003). The term mean reversion is defined as the phenomenon that stock prices tend to regress to the mean or average of prices over long periods when investors hold their assets for a long time (Investopedia, n.d.). As a result, returns and even interest rate would move to the mean. If investors buy stocks when the prices are increasing, they would eventually lose their money when the prices reverse to the mean (Malkiel, 2003). The graph below by Fama and French (1992) and Malkiel (2003) support the idea of mean reversion.

Figure 2.1: Daily mean reversion



(MarketSci, 2009, http://marketsci.wordpress.com/2009/08/10/the-state-of-short-term-mean-reversion-july-2009)

The idea of mean reversion was also found by other scholars including Fama and French (1988) and Poterba and Summers (1988). De Bondt and Thaler (1985) and Malkiel

(2003) also proved the similar phenomenon. First, De Bondt and Thaler (1985) found that the losing stocks, defined as those whose prices dropped over a certain period, tended to beat the market mean by around 20%, whereas the winners performed poorer than the market mean. They also noted that most investors overreacted to unpredicted news events. People overvalued new information too much in stock market. Malkiel (2003) also showed that the stock market did not perfectly perform efficiently. Nevertheless, he did not agree with the idea that the bias consistently made the market inefficient. He instead concluded that this finding was not a strong form of bias; No matter what patterns or strategies investors found, they could not make a profit persistently. Coversely, Jagadeesh and Sheridan (1993) found profitable trading strategies. That is, “trading strategies that buy past winners and sell past losers realize significant abnormal returns over the 1965 to 1989 period” (p. 89). They investigated the strategy based on past 6-month returns. Based on this result, it would be possible that sometimes winning strategies exist in the betting markets.

Market efficiency in the betting market and the bookmaker’s role

The EMH is also applied to the sports betting market in that the two markets have several similarities as mentioned. Also, economists’ justification for testing market efficiency of the betting market is that gamblers’ behaviors are analogous with those of investors in stock market (Borghesi, 2007). Thaler and Ziemba (1988) mentioned that the sports betting market is a better market in which to test market efficiency than the stock market because of the difference in the ending point of the event in the two markets. That is, the sports betting market has very clear ending point with every game whereas stock prices tend to live permanently. The basic idea in the sports betting market is that if the market is efficient, it is impossible for the bettors to make a profit consistently on average (Pankoff, 1968). Like investors in the stock market, bettors have access to public information, such as betting odds or game statistics, via the sports book and the leagues’ official websites. Thus, they are easily able to analyze and make their subjective viewpoint on the betting. However, based on the EMH, their own information would be useless, since all publicly available information is already in the betting odds (Zuber et al., 1985). If there is a tendency over a certain period that leads to inefficiency in terms of positive returns or winning percentage more than 50%, the betting market would be thought of as an inefficient market (Brown & Abraham, 2002). Previous studies also assumed that some evidence of inefficiency would be caused by bookmaker's roles

The bookmaker is an organization or a person that sets the betting odds. The bookmakers' dual roles have been discussed in previous literature. Summers (2008) and Gander et al. (2001) stated that the bookmakers attempt to avoid risk situations, losing their own money, as they try to equal the wagers on each team in a bet. In other words, if the amount of money wagered is placed equally on each side, the bookmakers earn the commission (Gander et al., 2001). In this situation, no matter which team wins the bet, they are not affected by the result. This is the dominant assumption for the bookmaker's function for testing market efficiency in the betting market. For instance, if the bettors wager on one team lopsidedly, 80-20 for example, then the bookmaker would try to move the betting lines against the team in order to balance wagers. However, if the original betting lines perfectly achieved an efficient market, then the altered lines would cause some unwilled biases and patterns.

There is another assumption for the bookmaker's role. Levitt (2004) and Paul and Weinbach (2011) suggested that the market maker is associated with the outcome of the bet. In other words, some of the bookmakers try to make the betting lines against the bettors' behavior in order to maximize their profits as well as to achieve the first function of balancing betting money. Sometimes the wagers can be placed asymmetrically if the majority of the bettors feel that the betting lines are not a good fit for the outcome of the bet. If the bookmakers know the tendency and set the betting lines in ways that are disadvantageous to the bettors, they could maximize their profits (Paul & Weinbach, 2011), since people's misperception would not easily change. Therefore, in this case, the bookmakers make some biases intentionally. For example, if the Chicago Bears (CHI) did not lose any games this season and covered the point spread many times, the bettors would have the misperception that CHI outperforms the market expectation, and finally the majority of them would wager more on CHI. If the bookmakers make biased betting lines that are disadvantageous to the bettors for CHI, the bettors would lose their money. Based on this example, it is possible that the bookmakers have an intentional bias regardless of the inefficiency. Levitt (2004) found that the bookmakers sometimes set the betting lines against the bettors' behavior. This role is different from the role of a specialist in the stock market, since the specialists match buyers and sellers whereas the bookmakers do not balance the wagers. As a result, it is possible that the sports books might correctly predict bettors' actions and purposefully set biased betting lines. Paul and Weinbach (2011) examined the bookmakers' role in the NFL betting market. They noted that the sports book that they tested had a large imbalanced betting volume in the point spread and the O/U betting market. Therefore, Paul and Weinbach (2011) supported Levitt's idea that the odds makers do not always try to balance the betting volume.

Horseracing

This section will introduce several previous studies in sports betting. Each betting market will be shown separately depending on which odds systems it uses. Many previous studies in sports betting have found some evidence of market inefficiency, although there might have been no consistent bias within each sport. Of all sports betting markets, horseracing has been a dominant area for testing the EMH. The racetrack employs the pari-mutuel system (Thaler & Ziemba, 1988) instead of the fixed odds system. The key characteristic of the pari-mutuel system is that gamblers never know the amount of the payoff until the race ends. Payoffs in the pari-mutuel system are determined by the amount of wagers, and they are calculated after the commission is deducted from the totals (Thaler & Ziemba, 1988) whereas in the fixed odds system, payoffs are not affected by the amount of wagers. For instance, let's suppose that total money wagered is $1000, wagers on horse number 5 total $100 and the commission rate is 15%. In this case, if the horse wins the race, the payoffs would be $8.50 (=1000(1-0.15)/100). Hence, if a bettor wagers $1 on the horse, profit would be $7.50 per $1. As indicated, payoffs per dollar and profit always depend on how much money is placed on each horse. Moreover, , Woodland and Woodland (2001) and Thaler and Ziemba (1988) noted that the commission for the market maker in horseracing is much higher, 15-20%, than in other kinds of sports betting, where the commission is below 10%.

At the racetrack, researchers have found a favorite longshot bias (Ali, 1977; Asch et al., 1982; Asch et al., 1984; Thaler & Ziemba, 1988; Williams & Paton; 1997; Cain et al., 2003; Sobel & Raines, 2003). A longshot in gambling indicates a horse, an individual player or a team that has very low chance to win but has a higher percentage of returns. Hence, the favorite longshot bias means that the bettors overestimate the winning probability of the longshots rather than that of the favorites regardless of the empirical probabilities (Sobel & Raines, 2003). The reason for the bias can be explained by the commission rate. Bettors can know that they cannot make positive returns from the bets on average because of the high rate of the commission. In addition, there are many recreational gamblers who are uninformed people. Thus, it is probable that they would like to maximize their utilities from wagering on longshots (Williams & Payton, 1997). As the favorite longshot bias has been found, the bettors are thought of as risk-lovers or risk-seekers (Sobel & Raines, 2003).

For the favorite longshot bias, Asch et al. (1982) also noted that the favorite longshot bias was more likely to occur in the late races although the favorites also had a much higher probability of winning in those races. They reasoned that because of the expensive commission, bettors had generally lost their money, and they expected to break even by large returns as they bet on longshots in the late races. In addition, psychologist Mcglothlin (1956) mentioned in his study about the bettors' choices on the uncertainty of outcomes that the bettors in the racetrack generally tended to like the combination of low probability and high prizes better than high probability and low prizes. Additionally, Williams and Payton (1997), for the favorite longshot bias, also assumed that the odds makers know the future outcomes with certainty. Based on this assumption, the bookmakers would maximize their profits by making longshots' odds to be seen like having a better chance to win the races than the actual outcomes, drawing wagers from gamblers.

Asch et al. (1982) also tried to find answers on whether or not there was a pattern for profitable betting and whether the betting odds were correctly predicting the race in terms of the order of finish. They found that the favorites usually tended to win the races, so the practice of betting on favorites was a 'good bet' whereas longshots did not win many of the races. This result implies that if the favorite longshot bias exists, the bettors have a false expectation and believe their own subjective information for betting rather than the public information or betting odds. The authors also found that at the racetrack, informed bettors existed, but they could not beat the market either. Finally, they concluded that there was not enough evidence of market inefficiency.

Regardless of the favorite longshot bias, Snyder (1978) noted that the racetrack betting market was highly efficient and it mirrored all publicly available information in the odds. He also assumed that the bettors tended to maximize their profits. Based on his assumptions, he could not find profitable strategies or biases in the betting market. He concluded that the bettors underestimated the actual probability of winning with horses with a lower winning percentage and lower odds. He also agreed with the favorite longshot bias. He explained that the bettors would not like to bet on favorites in that they did not satisfy the small amount of returns from the favorites because of the high rate of commission in the pari-mutuel system.

Major League Baseball Betting Market

Another sports betting market that does not use fixed odds system is MLB. As the first literature in the MLB, Woodland and Woodland (1994) tested market efficiency from the 1979 to 1989 seasons, and then compared their results with previous research in the racetrack market. According to the authors, baseball employs money lines and, unlike the fixed odds system, the amount of the commission depends on which team bettors bet. For example, when the bookmakers announce the money line as (-120, +110), the first money line is for the favorite and the other is for the underdog. Thus, the bettors earn $1 per $1.20 on favorite and $1.10 per $1 wager on underdog. If the MLB market is efficient, the bettors' expected returns are negative and equal to the commission (Woodland & Woodland, 1994). From this study, they found the reverse favorite longshot bias, the reverse phenomenon of the favorite longshot bias at the racetrack. This means that the bettors tend to overbet on the favorite and underbet on the underdog. However, the authors mentioned that the baseball market was highly efficient since the evidence was too small to reject the null hypothesis that the market was efficient. They concluded that bettors were not risk-lovers. The authors point out that the commission rate was also low in MLB around 2 or 3%. Thus, bettors do not need to bet on underdogs since the returns for the favorites do not have much deducted by the commission (Woodland & Woodland, 1994).

Woodland and Woodland (2003) updated the same test for the MLB for the 1990 to 1999 seasons. They found the same bias during the seasons and concluded that the reverse favorite longshot bias tended to occur permanently. They reasoned that the bettors were still quite informed compared to those in other markets. Again, concluded that MLB bettors do not need to be risk-lovers because the difference of returns between the favorites and the underdogs are not quite different.

Besides, Brown and Abraham (2002) investigated the O/U betting market for MLB games from the 1996 through 2000 regular seasons to see if there was a certain strategy that beat the market. In the O/U betting, the difference between the actual total scores and the expected outcomes offered by the bookmakers is not important only whether the total score is above or below the line (Brown & Abraham, 2002). The authors found that the Vegas line tended to show a certain bias. That is, it successively overestimated or underestimated the lines at some times. Brown and Abraham (2002) tested two strategies: bet on teams with winning streaks and bet against those teams. From the two strategies, they found that betting on a team with five or more consecutive wins beat the market and was profitable during the 1997 season, although this strategy was not successful for other seasons. Therefore, they concluded that the 1997 season was somewhat inefficient.

Lastly, Gander et al. (2001) examined the MLB betting market from the 1984 to 1999 seasons in terms of home field advantage. They assumed that the bookmakers tried to make a riskless profit by balancing the wagers on each side. They first found that there was no profitable strategy during the regular seasons combined nor with all postseason games combined. This result implies that the market makers reflect home field advantage in the betting lines. However, when they separated home teams into underdogs and favorites by season, in 10 of 15 seasons, the actual returns for the home underdogs were higher than the expected returns whereas the home favorites were not profitable. Nevertheless, the p-value of this result was slightly more than 0.05 ($p = 0.06$). Also, the authors found that for the post seasons, betting on home underdogs made positive actual returns but was not statistically significant ($p = 0.255$).

National Hockey League Betting Market

Woodland and Woodland (2001) first examined the NHL betting market from the 1990/91 season to the 1995/96 season. The authors tested if betting on home teams, away teams, favorites or underdogs was profitable and beat the market. They found some evidence of inefficiency. Betting on underdogs yielded higher returns on average than favorites. Moreover, except for the first two seasons, which were highly efficient, the returns for away underdog bettors were positive and statistically significant. They also extended the reverse favorite longshot bias of MLB into the NHL.

They also updated their examination for the NHL from the 1996/97 season through the 2006/07 season. Interestingly, the study concluded that there were no profitable strategies and even the reverse favorite longshot bias was eliminated (Woodland & Woodland, 2011. The elimination of the reverse favorite longshot bias was a remarkable finding in that baseball kept showing the same bias over the course of their study. Also, the same strategies, betting on underdogs and away underdogs, produced negative returns. The authors, therefore, concluded the recent NHL games were highly efficient. This result implies that the slight evidence of market inefficiency disappeared over the seasons so the same profitable strategies cannot be effective season by season (Sauer, 1998).

National Basketball Association Betting Market

The NBA betting market is the second largest sports league in terms of wagering volume (The Center of Gaming Research at UNLV, 2009). Some studies investigated whether bettors had overreactions to the recent information when they bet on the NBA. In fact, each outcome of sports games are not associated with each other because of random sequences like basketball shoots that are also independent (Camerer, 1989). Thus, the bettors should not overvalue the recent information. However, if the bettors misunderstand this independent sequence, it would be probable that they overestimate or underestimate certain teams in terms of winning streaks or losing streaks (Brown & Sauer, 1993). In this respect, Camerer (1989) and Brown and Sauer (1993) examined whether or not people misunderstood the random sequences and believed in “hot hand”.

For the first test regarding bettors’ misperceptions, Camerer (1989) assumed that “most people who watch basketball believe in the hot hand” (p. 1257). In his study, “hot hand” means teams on winning streaks, and “cold hand” indicates teams on losing streaks. If bettors believe in the hot hand and the bookmakers reflect this tendency, teams with the hot hand would perform poorer than market expectations and the forecast errors, the difference between the market expectations and the actual outcomes, would be negative. Moreover, if hot hand effect is true, the betting lines can be thought of as good estimates toward bettor’s action rather than that of the future outcomes. Camerer (1989) found that there was slight evidence of people’s mistaken belief in the hot hand, as teams on losing streaks tended to perform better than market expectations. This result can be related to the results by De Bondt and Thaler (1985), who found that losers in the stock market that lost their value over a certain period saw increases in their prices while investors overreacted to stocks of winner companies. Therefore, Camerer concluded that people did not seem to believe that the outcomes of basketball games were not random sequences and also that betting against teams on winning streaks could be slightly profitable.

Brown and Sauer (1993) and Paul and Weinbach (2005) also examined the hot hand effect and profitable betting strategies in the NBA. First, Brown and Sauer supported Camerer’s (1989) idea that the bettors believed in the hot hand and the point spreads mirrored this misunderstanding. Therefore, they supported the idea that the betting outcomes are independent. Paul and Weinbach (2005) tested if betting on double-digit underdogs (large underdogs) broke the efficient market from the 1995/96 to 2001/02 seasons. They first found that betting against the large favorite rejected the null of a fair bet, 0.5, although the strategy did not reject the null of no profitability. However, they recognized that betting on big home underdogs was a profitable strategy. The large home underdogs are usually the worst teams in the league because even if the bookmakers reflect home-court advantage in the point spreads, they are expected to lose with certainty whereas large road favorites are deemed as the best teams in the league (Paul & Weinbach, 2005). Based on this idea, Paul and Weinbach (2005) reasoned that the bettors overestimated the ability of large favorites when they were away teams. Also, they explain “fans and gamblers alike enjoy being associated with winners, not losers.” (p. 398). Thus, they might not want to bet on the worst teams even though they might outperform the market expectation because of home-field advantage.

Another explanation for the large underdogs’ winning is suggested. That is, the large favorites might not do their best in that game and they know that they can win the game with certainty even though they do not cover the point spreads (Paul & Weinbach, 2005). For instance, coaches of the big favorites might not want their star players to play for as much time. As they save the players, the team is preparing for the next game. This shirking by players and coaches is one reason offered as a possibility for the big underdogs’ winning the bet (Paul & Weinbach, 2005).

A similar finding was discovered by Paul et al. (2004) for the O/U betting market in the NBA from the 1995/95 to 2001/02 seasons. Although the overall data set supported the NBA as highly efficient, the authors found that the bettors preferred overs to unders. Especially for the highest totals, the null of a fair bet was rejected as unders tended to cover the point spreads more than 50% of the time, although it was not statistically profitable.

Gander et al. (2001) approached the concept of market efficiency by home-field advantage. They tested market efficiency with a z-test: if a team’s average winning percentage was higher 50% or 52.38%, winning strategies or profitable strategies would exist. They first found that home-court advantage existed in that home teams won more than 63%

of all games that they tested and home teams were set as favorites in 75% of all games. They also noted that the market did not misprice the advantage, since the home teams never won their bet statistically more than 0.5. However, when they separated the home teams by two types, favorites and underdogs, the result was different. Home underdogs won more than 54% of all bets from 1981/82 to 1996/97. Nevertheless, because of the small number of games for the home underdogs, they concluded that there was no remarkable sign of market inefficiency.

Another approach was used by Ashman et al. (2010). Their study investigated whether or not players' fatigue was included by bookmakers in betting lines. In particular, they wondered how the home teams' performance compared to market expectations in terms of the rest period. It might be a disadvantage to the home teams when they have fewer days off than the visiting teams, even if home-field advantage exists. Their main finding was that the market did not appropriately estimate the point spreads, overestimating the home advantage from 1990/91 through 2008/09. Especially when the home team had no rest period over two games and the visitors had one or two days off, the market continuously mispriced those games, underestimating the impact of player fatigue. The mispricing tendency was strong when the home teams played the first games on the road; when they independently tested the home underdogs and the home favorites, mispricing for the underdogs was magnified in that "home underdogs did much worse than home favorites in the home disadvantage situation" (Ashman et al., 2010, p.610).

National Football League Betting Market

There are many previous studies using the NFL as a setting for examining the fixed odds system. Like the NBA, the NFL betting market also employs the fixed odds system, and the odds makers should pursue a fair bet by the betting lines, such as the point spread (Wever and Aadland, 2010). Several studies have proved that the football market is highly efficient. There has been some dispute, however, over the efficiency of the betting market, a controversial issue on whether or not a certain season or game has some evidence of inefficiency. Studies such as Wever and Aadland (2010), Borghesi (2007), Summers (2008), Zuber et al. (1985) and Vergin and Scrabin (1978) found several patterns that resulted in market inefficiency whereas Dare and Holland (2004) discovered very little decisive evidence of bias that caused the inefficiency.

Researchers use two methods to test market efficiency. The first method is to study the relationship between market expectations and the actual outcomes by binary logit model, binary probit model or multivariate regression models (Dara and Macdonald, 1996; Zuber et al., 1985; Gray & Gray, 1997; Borghesi, 2007). For example, using a multivariate regression model, researchers investigate whether betting on the favorite or the underdog, or on the home team or the away team is profitable, and an independent variable can find evidence of inefficiency. Also, in the probit or logit model, they usually try to find whether the predicted probability for each team is higher than 0.5. The second method is to compare the mean of the actual outcome with the null hypothesis of a fair bet and profitability by the z statistic in order to find simple strategies. For example, if the observed mean of a favorite win the bet is 0.55, then it is compared with the null of fair bet, 0.5, and the null of profitability, 0.5238, in order to investigate statistical difference (Woodland & Woodland, 2000).

Pankoff (1968) was the first researcher who tested market efficiency in the football market (Vergin & Sosik, 1999) and he found no significant evidence for the inefficiency during the 1956 through 1965 seasons. Therefore, he concluded that although the bettors tended to maximize their profit like investors in the stock market, beating the market was impossible. Subsequent research by Vargin and Scriabin (1978) and Amoako-Adu et al. (1985) found some evidence of inefficiency in their data set. Vergin and Scriabin tested the NFL seasons from 1969 to 1974. They created their own intervals of point spreads: from 0 to 5, from 5 to 10, from 10 to 15, and over 15. Under the assumption that returns for favorites and underdogs were statistically equal, underdogs tended to cover the point spreads more often than favorites except the first interval, from 1 to 5. If teams were favored by 15 points or more, the null hypothesis was rejected at the 5% level. This result might have occurred because the bettors overestimate large favorites since they are usually the best teams in the league, and the bookmakers set favorable point spreads for the big underdogs in order to balance wagers against people's overestimation (Paul & Weinbach, 2005).

Amoako-Adu et al. (1985) approached the concept of market efficiency by comparing the closing lines with the actual outcomes and the opening lines with the closing lines. First, they used the simple regression model to see if the point spreads were good estimates of actual outcomes. By this examination, they found that there was very little association between the point spreads and actual outcomes at the 0.05 level. Thus, they concluded that the point spreads were not good estimates of game outcomes. Also, it was revealed that if people had technical strategies and bet on the opening and closing lines by their own strategies, they would obtain abnormal returns.

Unlike the above studies, Gray and Gray (1997) used another statistical method, the probit model, since they believed that the ordinary least squared (OLS) regression methodology was sensitive to outliers. In other words, in point spread betting, the number of points by which teams outperform the market expectation is not important, since winning by 1 point and 20 points are thought of as the same result (Gray & Gray, 1997). Thus, the authors employed the probit model, where the model showed only wins or losses. Among their findings, betting on the home underdog yielded positive returns even when the commissions were deducted. They also illustrated that people overreacted to teams' recent performances discounting teams' average performance. This result was the same as phenomenon in the stock market, where investors ignored past prices and overestimated the recent prices of stocks (De Bondt & Thaler, 1985).

Unlike simple betting strategies such as only betting on underdogs or home teams, Borghesi (2003, 2007) tested whether or not the market fully reflected all available information in the point spreads. His first finding was that late in the season the bettor tended to overbet on away teams and home teams usually outscored away teams by 3.03 points on average (Borghesi, 2003). He noted that the point spreads in the final weeks were especially favorable to home team bettors. The reason for the bias late in the season would be caused by betters' tendencies that overbet on away teams, since the bookmakers would try to balance wagers and finally made the betting lines against away team bettors. Consequently, home teams won games by 4.46 points, which was statistically significant at 1% level, whereas the average market expectation was 2.40.

Also, it is possible that team performance could be affected by environmental elements such as temperature, rain or snow, and people would consider these factors when they wagered on certain teams. This behavior can be related to the investors' behavior in stock market, in that trading tends to be influenced by environmental conditions like temperature of the day (Borghesi, 2007). Borghesi (2007) mirrored this environmental effect into the football betting market to see if the market expectation had a certain bias. He hypothesized that the weather effect could be related to the betting prices, and the prices might not be fully reflected in the betting lines. The reason for his hypothesis was that football is usually played in open-air stadiums and the teams play anytime regardless of the weather conditions (Borghesi, 2007). Also, he further hypothesized that home teams have better acclimatization to home town weather conditions than visitors. So, if the market is efficient and fair, this kind of factor should be considered by the odds makers when they set the market prices. He compared games in cold weather with games in hot weather and found that cold weather negatively affected visiting teams more than hot weather in terms of performance. In addition, as the temperature decreased and the home team acclimatized to the weather conditions, the home team was more likely to cover the spreads. Additionally, when people bet on the home teams in the coldest temperatures, the winning rate was statistically significant at a 1% level. Therefore, home teams playing in the coldest region were underpriced (or away teams from warmer places were overpriced). He also reasoned that away teams were affected more by cold weather than warm, so being away from home could decrease the morale of visiting teams.

Paul and Weinbach (2011) approached the EMH using point spreads and totals (O/U) gathered from several sports books to investigate the possibility of a certain bettors' bias in the NFL. Unlike the assumption that the sports books try to balance wagers on each side, they found that some of the bookmakers did not show this tendency. They sometimes set skewed betting lines and kept these lines until the market was closed. In particular, among the sports books that they tested, Sportsbook.com was found to have very imbalanced betting lines. Thus, the authors concluded that the sports books sometimes made biased betting lines intentionally, in order to maximize their profits if they know the bettors' propensity. This result is similar with that of Levitt's (2004) study that the odds makers move or set the lines against people's gambling tendencies. The authors also proved that the bettors overbet favorites on the road more often than underdogs at home. This is evidenced by as the point spreads or totals increased to a favorable position for the favorites, the percentage of wagering on favorites increased as well. They illustrated it would be profitable to bet against this tendency.

There are many sports books in Nevada and they usually announce similar betting lines. However, there might be patterns for each sports book since they do not move the lines the same amount from the opening lines to the closing lines. In this respect, Summers (2008) tried to find certain patterns in the lines offered by several sports books (Hilton, Las Vegas Line, and Mirage) from 2003 to 2007 and investigated whether or not each sports book had a certain pattern. First of all, the author revealed that in 2003 the returns of the bettors for the home team with the opening lines at the Mirage was higher than break even, although the strategy could not reject the null of profitability. Also, winning strategies were different from season to season. Those strategies, such as betting on the home team or on favorites, were not statistically profitable. However, when the point spreads were changed by at least 3 points from the opening lines to the closing lines and people wagered for middles, which bettors bet both for and against the same team, it would be possible that there was a profit made by plying for the middles. Nevertheless, the author mentioned that a 3-point change did not occur frequently (5.5% of the data set), so there might be few chances to bet on this kind of game.

Although many researchers found some simple strategies, like betting on large underdogs or large home underdogs (Paul and Weinbach, 2005), the overall result of these profitable or winning strategies was not persistently successful or statistically significant (Asch et al., 1982). Also, the football betting market is thought of as a highly efficient market (Woodland & Woodland, 2000), so even if a certain pattern is found at a certain time of the season, the pattern will disappear the next season or be distinguished over time (Gray & Gray, 1997). Also, the high variability of winning percentages and small sample sizes could result in low explained variance, so it is important for researchers to study many seasons in order to draw more accurate conclusions (Osborne, 2001).

Home Field Advantage across Professional Sports

In sports leagues, there are always home teams and away teams in each game. Many people believe that the home team has more advantages than the away team For example, if players feel more comfortable in familiar weather, especially extremely cold or hot temperatures, players not used to that weather could be negatively affected by this weather condition emotionally and physically (Borghesi, 2007). The home field advantage has been well established by many studies (Clarke & Norman, 1995; Steendland & Deddens, 1997; Carmichael & Thomas, 2005; Forrest et al., 2005; Simon & Simonoff, 2006; Borghesi, 2007). Aside from weather conditions, there are other dominant factors that can be thought of as home advantage: familiarity factors, travel factors, referees' favorable decisions to the home team or rules factors, and the crowd factor (Carmicheal & Thomas, 2005). First of all, a familiarity factor can be associated with the home field and its playing surface (Vergin & Sosik, 1999). Every field might have different ground conditions possibly because of climate or the type of grass. Thus, it is possible that it could take a long time for away team players to adapt themselves to the unfamiliar environment.

The second factor, traveling, could affect team performance because of fatigue, breaking players' routines (Nevill & Holder, 1999), and different time zones between home and away (Preez & Lambert, 2007). Away team players have to travel long distances, and even they can waste a day of practice due to the journey (Koyama et al., 2008). Also, home teams can have more days for rest or practice since they just stay their home town. However, this factor has been discovered to be a minimal advantage, even if the traveling factor has an impact on team performance.

Other advantages, rules, and crowd factors are also documented well. Carmichael and Thomas (2005) mentioned the special privilege in baseball and soft ball that the home team has last bat. This chance of the last offense might be beneficial to the home team emotionally. Also, the crowd factor, such as support from large crowds, can encourage home team players to show better performance. Noise from home fans can intimidate or annoy the visiting team and the sound can bother the visitor's performance. Moreover, this crowd factor may influence referees' decisions to the home team's advantage (Carimichael & Thomas, 2005). In the English Premiership, referees' decisions on penalties and injury time at the end of the game were favorable to the home team (Sutter & Kocher, 2004). Referees' decisions on penalties are very important, since they are decisive calls to directly increase a team's probability of winning. According to Sutter and Kocher (2004), "85% of penalties result in goal" (p. 468), so the home team had more chance to score by penalty kicks. Schwartz and Barsky (1977) compared home advantage for each sport league. They found that home field advantage was higher in indoor sports like ice hockey than in outdoor sports and that there was the least advantage in baseball.

There are also several studies of home advantage in terms of market efficiency in sports betting. Vergin and Sosik (1999) tested the NFL's market efficiency from 1981 through 1996. They focused on Monday night games and playoffs. In these games the home team received a lot of attention from the local and even national media, so tickets were often sold out for these kinds of games because of the increase in fan interest. Players could be positively motivated by this attention. Bookmakers made 67% of the home teams in these games the favorites. They found that the bettors for home underdogs were profitable when they tested home favorites and home underdogs separately, whereas betting on the home team was not profitable strategy. They reasoned that in general, the bettors and the bookmakers recognized and reflected this factor in the point spread. In addition, bettors might overestimate the home favorite, so bookmakers set the betting lines against this tendency; people underestimate the home underdog since the underdog is expected to lose even if there is home advantage. This result was similar to Paul and Weinbach's (2005) findings when they discovered that betting on large home underdogs in the NFL could be a profitable strategy. The reason that large home underdogs can be profitable is that the team is among the worst team in the league. Bettors might not want to bet on big home underdog because "fans and gamblers alike enjoy being associated with winners, not loses" (Paul & Weinbach, 2005, p. 395). Gandar et al. (2001) could not extend the same profitable strategy to the NBA and MLB betting markets.

The Effect of Rest Period on Player Performance

Ashman et al. (2010) investigated the NBA betting market efficiency in terms of the home team's rest period, particularly a home team's back-to-back games. They called this home disadvantage situation. They studied how home disadvantage situation affected the betting outcomes and the market efficiency. The researchers found that when the home team had back-to-back games and the away team rested for one or two days, the market mispriced the home team spreads. The home team only covered the spreads 45.45% of the bet, which rejected the null of a fair bet ($p = 0.002$), although there was little evidence of profitability ($p = 0.068$). This bias was worse when the home team played the first game of consecutive games on a road. They reasoned that fatigue made the home team timid. Therefore, it was discovered that there was a home disadvantage situation if the home team had fewer days off than the visitor and based on Ashman et al.'s results, the bookmakers would not seem to consider fatigue factor in the point spreads.

Entine and Small (2008) also examined the role of rest in the NBA in terms of home advantage. NBA teams sometimes play consecutive games. However, home teams usually avoid this schedule, whereas away teams tend to have tighter schedules (Entine and Small, 2008). Thus, Entine and Small investigated the possibility of home team advantage when the home team has more days to rest than the visiting team in terms of the margin of victory. They demonstrated that home teams that had three or more days of rest improved the margin of victory.

Unlike an NBA team that sometimes has back-to-back game, an NFL team usually plays on a weekly basis and most of the games are on Sunday. Sometimes, an NFL team has shorter break than a week if the team is playing a Thursday or Monday night game. Each team also has a bye week, which is one week off. The bye week offers the opportunity for players to recover from fatigue. Players who enjoy this vacation could perform better than their opponents. Thus, changing players' routines by shorting the time between games or by adding a bye week could negatively or positively influence team performance or game outcomes. Of 17 weeks, teams play 16 weeks with one bye week sometime between week 4 to week 10. Sometimes one team can have a bye week and then play another team that has not yet had a bye week or already has had a bye week, while other times both teams have a bye week at the same time before playing each other. For NFL players, one game per week is their routine, just as most people work five days per a week as their routine. Psychology literature illustrates that relaxation from work has a positive effect on people's performance when they come back to work. Fritz and Sonnentag (2005) mentioned that vacations or days off from work were beneficial to organizations as well as workers. Also, they contended that performance could be reduced by high daily job demand. In other words, vacations or days off from work are necessary for people since recovery during a vacation can positively affect performance in the long run (Sonnentag, 2003). Football is thought of as one of the toughest sports. Thus, a bye week may have a positive impact on team performance in that exhaustion and burnout can be diminished due to the break. In fact, Etzion (2003) stressed that people took a vacation for a certain amount of time had less stress and burnout than those who did not have a vacation. These results from studies in psychology can be applied to football players in terms of rest from their work place and improved performance after their bye week. It follows that if the bye week affects their performance, the bookmakers should reflect these factors in the betting lines.

CHAPTER 3

RESEARCH QUESTIONS

Previous literature found some winning or profitable strategies, such as betting on underdogs, home underdogs or large home underdogs in NFL wagering market. Based on previous studies, the first question of this thesis is whether or not there is a possible simple betting strategy that beat the market and whether or not the same betting strategies in previous literature are still effective. For testing simple strategies, we can break NFL teams into four categories: home favorite (HF), home underdog (HU), away favorite (AF) and away underdog (AU). Among the four categories of teams, the HU would still be a possible winning strategy like findings of Gray and Gray's (1997) study, or it is possible that the other teams would have a bias in the recent NFL betting. However, if this study finds a winning or a profitable strategy for the HU, there would a reason for this tendency. That is, if the HU has a bias, it means that the bettors might not like to bet on the HU, since most of the teams might be among the worst in the league. Or, as Paul and Weinbach (2005) noted for NBA betting market, people in the NFL might also want to draw utility from the AFs, which is the obtained total satisfaction from their betting, since they could be usually among the best teams in the NFL and they would also want to be associated with the winners (Paul & Weinbach, 2005). In this manner, they would overestimate the chance to win with the AFs in the bet. Moreover, because the market makers are experts who predict future outcomes, they are confident about the bettors' betting tendencies in advance. They would move or set the betting lines against the bettors' slanted betting behavior toward the AFs, in order to balance the wagers or maximize their revenues by decreasing the chance to win with the away favorites (Paul & Weinbach, 2011).

Also, there might be biased patterns when AUs play HFs. As noted in previous research related to home-field advantage, it was discovered that several home field advantages exist (Carmicheal & Thomas, 2005). These effects are also mirrored in the betting lines (Vergin & Sosik, 1999) in that home teams would be set more often as favorites than teams on the road. However, if the AUs win many more bets than the HFs do, it is possible that the bookmakers overestimate the ability of the HFs or the home-field advantage. Conversely, if the HFs win more bets compared to the winning percentage of the AUs, it is probable that the market makers undervalue the effects of home-field advantage.

The second research question is whether a bye week is considered by the EMH. As mentioned earlier, the rest period affects people's work performance. Unlike the NBA, NFL teams usually have the same amount of days off between their games so NFL has a clearer rest period than NBA. They also have one bye week during the season, so the bye week can be thought of as a long term break from the work-place. Moreover, during the bye week, teams may try to improve their play and strategies to show better performance immediately after the bye week. In this respect, the bye week would positively have an effect on their performance. If the market is efficient, the bye week should not play a role in market inefficiency as the point spread should reflect all public information. If the games after the bye week are also efficient, the four categories of teams have an equal probability of betting success. Specifically, if the HFs' win rate is different than break even, it is possible that the bookmakers miss or underestimate the effect of the bye week on player performance. Therefore, if HF, HU, AF or AU experiences a higher than expected win rate after their bye week, then it may be evidence of inefficiency in the NFL betting market.

To summarize, this thesis will investigate the relationship between market expectations and the actual game outcomes, whether or not there is a simple strategy that can beat the NFL betting market, whether or not the betting strategies in previous studies are still effective, how market makers respond toward vacations, and whether or not the bookmakers consider the effect of rest when they set the point spreads. This study is important in that the betting market should pursue or maintain a fair market and an efficient market (Wever & Aadland, 2010). Also, a potentially interesting aspect of football betting has received little attention compared to basketball betting: the effect of rest period on game outcomes and betting outcomes. This factor would be new and important, since all NFL teams have their bye week as vacations. If this rest impacts performance, then it should be reflected in the betting lines. Moreover, if the results of this study show that there has been a possible profitable strategy that causes inefficiency, we should consider why the market is not efficient. The next section will discuss variables that will be used in statistics tests and shows summary of the data collected.

CHAPTER 4

DATA and METHOD

Data

The data set used in this thesis information on each NFL regular season game from 2002 to 2009. The reason for starting analysis of this study with 2002 is to create a balanced panel data set, because the Houston Texans (HOU) joined the league in 2002. Variables in the data set are listed below. Some of them, such as the closing lines (point spread), were directly gathered from covers.com. sportsinsight.com, and computer sports world. Other variables were calculated from the raw data. Finally, the point spreads were drawn from the closing lines instead of the opening lines in order to maintain consistency, since the point spreads are sometimes moved by the bookmakers until the market is closed. The variables are listed below in detail (Table 4.1).

Table 4.1: Variables

Year	Each season from 2002 to 2009
Week	The regular season from week 1 to week 17
Pick'em	There is no favorite team and underdog team, so winner of the game also wins the bet. The closing line is 0.
Push	The closing line and the actual score difference between a favorite and an underdog are the same. In this case, all wagers are supposed to return to the bettors.
BYE	A game after each team's bye week. This is a dummy variable, so the value will be 1, if the team plays after their bye week.
AF	This is a dummy variable to show whether or not the away team is set as the favorite. If it is the favorite, the value will be 1.
HF	This is a dummy variable to show whether or not the home team is set as a favorite. If it is the favorite, the value will be 1.
Away	Team on the road

Table 4.1 (cont.)

Home	Team plays at their home-field
CL	The closing line for each team
Fav Und	The actual score difference between the favorite and the underdog. If the underdog wins the game, the value will be negative.
Total	Actual total score by both teams
Forecast Error	The score difference between the closing line and the actual score difference
Winbet	A dummy variable for whether or not a team wins the bet (win=1, lose=0)
CL Interval (CL_INT)	The subjective interval of the point spreads for this study (Coded 0 from 0 to 5, 1 from 6 to 10=1, and 2 for more than 10

Each NFL team plays 16 games, and there are 32 teams in NFL. Thus, the size of the data set will be 2,048 games for the regular seasons. Before discussing the methodology of this study, the summary statistics would be helpful to see overall information of the data set.

Table 4.2: Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Closing lines	2048	0	24.0	5.569	3.5397
Favorite-Underdog	2048	-37.0	59.0	5.858	13.9654
Forecast error	2048	0	49.5	10.556	8.3103
Pick'em	16	1	1	1.00	.000
Push	62	1	1	1.00	.000

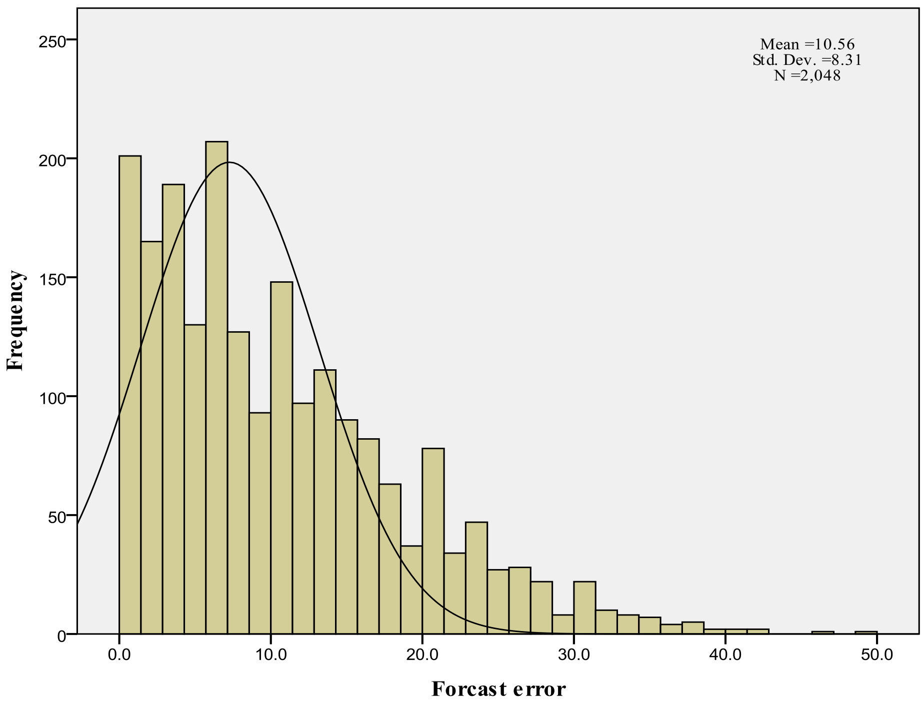
Table 4.2 shows the overall summary statistics. The total cases are 2,048 games including 16 games of the pick’em and 62 games of the push. Through 8 years, the maximum of the point spread (absolute value) is 24. As Table 4.2 shows, the closing lines are skewed; the standard deviation is low and mean is 5.5 whereas the maximum is 24. Interestingly, the forecast error variable shows 49.5 in maximum. This figure is quite large. Thus, the forecast error was summarized as quartiles below to see distribution of the error.

Table 4.3: Forecast error

Valid		2048
Missing		0
Mean		10.556
Median		9.000
Std. Deviation		8.3103
Minimum		.0
Maximum		49.5
Percentiles	25	4.000
	50	9.000
	75	15.000

Compared to Table 4.3, Table 4.4 shows that the errors are primarily less than 15 when we see the percentiles, and the median is 9. Although the mean is 10.6, it is somewhat larger than the median; the median might be meaningful since this data is highly skewed to the right (Figure 4.1). Thus, the mean can be affected more by outliers like the maximum value.

Figure 4.1: Histogram for Forecast Error



Next, Table 4.5 also shows the distribution of the closing lines. The range of each interval is 5. More than 50% of the closing lines for the data set were from 0 to 5, and there were not many games with large closing lines (10% of the closing lines).

Table 4.4.: Closing lines Intervals

	Frequency	Percent	Valid Percent	Cumulative Percent
0-5	1053	51.4	53.5	53.5
6-10	710	34.7	36.0	89.5
11-	207	10.1	10.5	100.0
Total	1970	96.2	100.0	

Lastly, Table 4.5 shows how often home teams were set as favorites from the 2002 to 2009 seasons. 67.2% of home teams were favorites, so the tendency that home teams were thought of as favorites occurs consistently.

Table 4.5: Home & Favorite Frequency Table

			Underdog	Favorite	Total
Home team	Away team	Count	1325	645	1970
		%	67.2%	32.8%	50.0%
	Home team	Count	645	1325	1970
		%	32.8%	67.2%	50.0%
Total		Count	1970	1970	3940
		%	100.0%	100.0%	100.0%

Method

There are two statistical methods, binary logistic regression and a significance test for a proportion that could be used for this thesis. However, this thesis will only employ one of them, the significance test for a proportion, to see if the NFL betting market is efficient. Gamblers' probability of winning is 0.5. Under the assumption that the NFL betting market is a fair and an efficient market, any betting strategies should not win more than a probability of 0.5. The expected returns should theoretically be 0 on average in the absence of a bookmakers' commission no matter which team bettors bet. For that reason the sport bookmakers set commission in order to guarantee their profit. Accordingly, because of the commission, the bettors' expected returns should be negative. As mentioned, the NFL employs an 11/10 rule for gambling (Vergin & Scriabin, 1978) so the equation below explains a fair market assumption based on the 11/10 rule:

$$\mathrm{P}\cdot\$100+(1-\mathrm{P})(-\$110)=0 \tag{1}$$

where P is the probability of winning, and 1-P indicates that of losing. \$100 and -\$110 correspond to profit and loss when gamblers wager. When we substitute 0.5 for the P in the equation above, we will see -\$5 in right hand side, not 0. This shows how a 0.5 winning probability does not constitute breaking even. Thus, every person is supposed to lose \$5 per bet on average, even if the ideal return in the fair market is theoretically zero.

From the equation, we calculate P as 0.5238 since P=11/21. This implies that the rate that breaks even is 0.5238, not 0.5. Therefore, people must win more than 52.38% of the bets on average in order to break even.

For the significance test for a proportion, there are four categories of teams, HF, HU, AF, and AU. Based on the knowledge of the required rate for profitability and the team category, the test will be conducted to investigate whether a simple betting strategy, which is to wager on only one team, would be statistically inefficient during the regular seasons. The statistically significant results will indicate that the chance of winning with this simple strategy is statistically higher than 0.5. If a certain inefficient result is found, then the strategy will be tested to see if it has a winning rate greater than 0.5238, which will be called as an economically inefficient result if it is statistically higher than 0.5238. It is also called a profitable strategy since people would make a positive return. Specifically, the teams of independent variables are categorical variables and all the teams will have binary outcomes in terms of whether or not they win the bet, coded 1 for a win and otherwise zero.

To examine the significance test for a proportion, there are several assumptions that should satisfy: type of data, randomization, population distribution, and large sample size (Agresti & Finley, 2008, p 144.). The data should be either quantitative or categorical and the data set used for this study satisfies this condition since the response variable will be shown as the binary outcome, win or lose. The independent variables are also categorical data except the closing lines and variables related to scores. Randomization means that the sample should be selected by a random process. For this thesis, the data set from 2002 to 2009 is the same as the population, and all observations will be tested. In addition, for the population distribution and large sample size, the sample size of this research has to be quite large since the sample distribution should approximate a normal distribution where mean and standard deviation are 0 and 1. In general, the sufficient sample size for the significance test for the proportion is at least 20, so the much larger size of the data set for this thesis, 2048, satisfies this assumption as well (even with, 62 push games and 16 pick'em games excluded). In all, 1970 games within the population will be tested, and this size of the data set still satisfies the assumption of the large sample.

Next, for null hypotheses, all observed proportions of winning will be converted into the z test statistic, in order to compare the proportions with a critical proportion of the null hypothesis in terms of the null hypothesis of a fair bet and profitability. First, the null of a fair bet is

$$H_0 : \pi = 0.5,\ H_a : \pi \neq 0.5 \text{ or } H_a < 0.5 \text{ and } H_a > 0.5$$

π is denoted as the critical proportion of the fair bet, and the test will be a two tailed test. In football games, HF always plays AU, and HU plays AF, so HF's and HU's probability of winning are correlated with the proportions of AU and HU. By definition if P is HF's win proportion, 1-P is AU's win rate. Therefore, it does not necessary that all team categories are tested.

After the test of the null of the fair bet, the strategies that can reject the null hypothesis above will be compared with the null of profitability, 0.5238. The null hypothesis and the alternative hypothesis for profitability are

$$H_o : \pi = 0.5238,\ H_a : \pi > 0.5238$$

Unlike the first significance test, this examination will be a one tailed test, since we only need to know whether or not a win probability exceeds 0.5238. Also, α-levels for these two significance tests are: 0.01, 0.05, and 0.10. In order to reject null hypotheses, p-values from the tests should be lower than these α levels.

For calculating the z test statistic the standard error of the sampling distribution should be calculated first by the population proportion, π. The standard error is

$$\sigma_{\pi} = \sqrt{\pi(1-\pi)/N} \tag{2}$$

where N is the total sample size and π is the population proportion, 0.5 and 0.5238. Therefore, we can finally the Z scores below

$$Z = \frac{(\pi - \pi)}{\sqrt{\pi(1-\pi)/N}} \tag{3}$$

where π is the actual win rate of the teams.

Based on the z values, the overall season outcomes for each team are first examined. It will show the recent NFL betting market's efficiency at once, and whether there has been a consistent bias in the NFL. Next, the each team's win rate for each season and each week will be tested. From these examinations, it would be expected to find some tendencies season-by-season and week-by-week, such as a team that usually tends to cover the spreads in a certain time. In fact, Borghesi (2003) noted that profitable strategies tended to occur at the end of seasons. Thus, it is possible that the comparisons of each season and each week might show similar results late in the season or new tendencies. Also, each interval of the closing lines

(CL_INT) will be tested to see if there is a certain tendency according to the amount of the closing lines. The test for each CL_INT is similar to that of Vergin and Scriabin's (1978) study (although they tested four intervals). Past research also found a profitable strategy of betting on the large underdogs (Paul & Weinbach, 2005), so the results from this section could be compared with previous research, seeing if the large underdogs still have a bias in the data set of this thesis. Lastly, the significance test for all games after teams' bye week will be conducted to see if the EMH of NFL betting market is violated after the bye week.

Besides, for another possible statistical method, the binomial logistic regression model (logit model) could be used for this thesis, which has only binary or dichotomous outcomes in dependent variables such as yes or no, or success or failure. As a probability model, it is employed when people want to study how much an independent variable affects a dependent variable in terms of probability. Thus, by using the logit model, we could know the predicted probabilities for each situation and how independent variables affect a dependent variable. The logit model is the transformed linear probability model for the binary response variables, where the results fall between 0 and 1. The basic formula for the model is

$$\log\left[\frac{P(y=1)}{1-P(y=1)}\right]=\alpha+\beta_k x_k \tag{4}$$

where the left hand side is the odds transformed by natural logarithm and in the right hand side, α is constant and β is a regression coefficient for each x variable. The reason for using the logit model instead of the linear regression model is that the linear model may not be an optimal process, since the response variable tends to be more than 1 in the linear regression. Agresti and Finley (2008) also noted that binary outcomes are examples of discrete variables, so the normal distributions are not optimal for models with discrete responses. Moreover, we just need to know whether or not teams win the bet in this study, not the actual score difference. The linear regression is also affected by extreme outliers as noted by Gray and

Gray (1997), so it would be inaccurate for sample estimation. Another characteristic of the binary logit model is that it utilizes maximum likelihood estimation, which means that "if the parameter equaled that number (the value of the estimate), the observed data would have had greater chance of occurring than if the parameter equaled any other number" (Agresti & Finley, 2008, p. 109), so the estimation would be thought of as a powerful predictor. Thus, the methodology is applicable to this kind of study to see if a team wins the bet and how high the win probability of each category of team is.

However, the logit model might be unable to be employed for this thesis since all independent variables are dummy variables, just explaining yes or no. The independent variables may also be able to have high correlation because home teams are usually set as favorites and away teams are set as underdogs. Accordingly, there would be high correlations between independent variables except a bye week variable because of the nature of the data set, and finally multicollinearity issues would be present in the data set. Therefore, the significance test for proportions would only be useful for this thesis.

CHAPTER 5

RESULTS

Statistical inefficiency

In this section, all variables for examining simple betting strategies - home team (HOME), away team (AWAY), favorite (FAV), underdog (UND), home favorite (HF), away favorite (AF), home underdog (HU), and away underdog (AU) - were tested by the significance test for a proportion. Tables provide the results based on a statistically significant bias and HOME, HF, and HU. This is because one team's win probability (WP) is the same as the other team's loss probability (LP). If there is some evidence of inefficiency found, that teams' results will be shown for a clearer description.

Overall, the NFL betting market was found to be highly efficient from 2002 to 2009. HOME-AWAY, FAV-UND, HU-AF, and HF-AU did not show any evidence of inefficiency. As an example, Table 5.1 reveals that the HOME WP averages 0.49 which has a large p-value (0.199). By betting on HOME, we could not expect a statistically higher WP than 0.5 and make positive returns, since there would be no pattern of the HOME-AWAY category when all seasons are combined.

Table 5.1: Home & Away (2002-2009)

		Category	N	$\hat{\pi}$	$\pi.$	P-value (2-tailed)
Home	Win	1	956	.49	.50	.199[a]
	Lose	0	1014	.51		
	Total		1970	1.00		

a. Based on Z Approximation.

Next, the total data set was tested by each season, week, and three ranges of the closing lines (CL_INT) to detect certain patterns. First, each season was independently tested by all game categories. Like the significance test for the overall data set, there was no bias detected. HOME WPs were statistically the same with 0.5 as the null hypothesis in each season (Table 5.2). No matter which team we wager on between the HOME and AWAY teams, it would be not possible to beat the market. For the HOME-AWAY, the highest WP was 0.55, by AWAY in 2008, but it could not reject the null hypothesis (p = 0.128).

Table 5.2: Home team & Away team (each year)

		Category	N	$\hat{\pi}$.	π	P-value [a] (2-tailed)
Home team (2002)	Win	1	122	.49	.50	.849
	Lose	0	126	.51		
Home team (2003)	Win	1	119	.50	.5	1.000
	Lose	0	118	.50		
Home team (2004)	Win	1	128	.53	.50	.441
	Lose	0	115	.47		
Home team (2005)	Win	1	125	.51	.50	.798
	Lose	0	120	.49		
Home team (2006)	Win	1	121	.49	.50	.704
	Lose	0	128	.51		
Home team (2007)	Win	1	128	.51	.50	.801
	Lose	0	123	.49		
Home team (2008)	Win	1	112	.45	.50	.128
	Lose	0	137	.55		
Home team (2009)	Win	1	144	.54	.50	.228
	Lose	0	114	.46		

a. Based on Z Approximation.

Nevertheless, the EMH is somewhat violated by the FAV-UND category for each year. Of eight seasons, three seasons show certain skewed betting results, two for UNDs and one for FAVs. Although the FAV-UND category does not show any evidence of inefficiency in the overall data set, UND tended to beat the spread in 2002. In that season, the underdog won 142 bets, 0.57 of its WP, significant at the 0.05 of α level (Table 5.3). It also showed evidence of inefficiency in 2006 by winning 142 bets (WP=0.57) which was significant at the same level.

Table 5.3: Favorite & Underdog (each year)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Underdog (2002)	Win bet	1	142	.57	.50	.026**
	Lose bet	0	106	.43		
	Total		248	1.00		
Underdog (2003)	Lose bet	0	120	.51	.50	.897
	Win bet	1	117	.49		
	Total		237	1.00		
Underdog (2004)	Lose bet	0	122	.50	.50	1.000
	Win bet	1	121	.50		
	Total		243	1.00		
Favorite (2005)	Win bet	1	141	.58	.50	.021**
	Lose bet	0	104	.42		
	Total		245	1.00		
Underdog (2006)	Lose bet	0	107	.43	.50	.031**
	Win bet	1	142	.57		
	Total		249	1.00		
Underdog (2007)	Lose bet	0	130	.52	.50	.614
	Win bet	1	121	.48		
	Total		251	1.00		
Underdog (2008)	Lose bet	0	125	.50	.50	1.000
	Win bet	1	124	.50		
	Total		249	1.00		
Underdog (2009)	Lose bet	1	128	.52	.50	.657
	Win bet	0	120	.48		
	Total		247	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

The null was also rejected at 0.05 with respect to FAV in 2005. This bias might be unique compared to previous studies that found that UND usually showed a bias. For instance, Gray and Gray (1997) and Vargin and Scriabin (1978) found that the HU tended to be a winning strategy that beat the market more often than its opponent, and it was sometimes profitable as well. However, the bias in this thesis was FAV.

Next, the HU-AF and the HF-AU categories were tested in each season. Of the categories, only the AF in 2005 (Table 5.4) showed a significant result of winning, even though the HF also won more than 50% of bets in 2005 (56%, p = 0.126). The AF won as many as 45 bets which is 0.61 of WP and significant at the 0.1 level (p = 0.81). Thus, although the HF is not statistically significant, it is apparent that the FAV (Table 5.3) tended to be a winning strategy, and the AF and the HF significantly contributed to the favorite bias in 2005.

Table 5.4: Away Favorite & Home Favorite (2005)

		Category	N	$\hat{\pi}$.	π.	P-value (2-tailed)
Away favorite (2005)	Lose bet	0	29	.39	.50	.081[a]
	Win bet	1	45	.61		
	Total		74	1.00		
Home favorite (2005)	Win bet	1	96	.56	.50	.126[a]
	Lose bet	0	75	.44		
	Total		171	1.00		

a. Based on Z Approximation.
*0.1, **0.05, ***0.01

Regarding tests for each week combined from 2002 to 2009, there are few biases detected. In the HOME-AWAY category, as Table 5.5 shows, the AWAY beat the market only in week 16, winning 72 bets or 0.59 of WP (p = 0.71). However, other weeks like week 15 and week 17, which also would be thought of as late in the season, did not reject the null hypothesis. By that point in the season, many teams' playoffs possibilities were already determined, complicating the bookmakers' ability to predict future outcomes. Still, week 15 and week 17 did not show any evidence of inefficiency.

Table 5.5: Home & Away (late in the season)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Home team (week15)	Win bet	1	60	.48	.50	.721
	Lose bet	0	65	.52		
	Total		125	1.00		
Away team (week 16)	Lose bet	0	51	.41	.50	.071*
	Win bet	1	72	.59		
	Total		123	1.00		
Home team (week17)	Win bet	1	64	.52	.50	.788
	Lose bet	0	60	.48		
	Total		124	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

In the same week, Table 5.6 reveals that the null hypothesis of a fair bet is also rejected for UND in the week 16 (WP = 0.60, p = 0.03).

Table 5.6: Favorite & Underdog (each week)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Underdog (week9)	Win bet	1	64	.60	.50	.041**
	Lose bet	0	42	.40		
	Total		106	1.00		
Underdog (week16)	Win bet	1	74	.60	.50	.030**
	Lose bet	0	49	.40		
	Total		123	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

From this result, it might be expected that AU rejects the null of the fair bet in the same week. The result of this expectation will be shown later. Turning back to UND, in week 9 across all seasons in the data set, the UND won 60% of 106 bets (p = 0.041).

Looking at the intersection of HOME-AWAY and FAV-UND (HF-AU and HU-AF), the AF in week 12 aggregated shows almost 0.67 of WP (Table 5.7), and it rejected the null hypothesis at the 0.1 level.

Table 5.7: HU & AF (each week)

		Category	N	$\hat{\pi}$.	π.	P-value [a] (2-tailed)
Away favorite (week12)	Lose bet	0	13	.33	.50	.053*
	Win bet	1	26	.67		
	Total		39	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

As expected, the AU in week 16 is discovered as a winning strategy (Table 5.8). Of 87 observations, it won 55 bets (0.63 of WP), and was significant at the 0.05 (p = 0.018).

Table 5.8: HF & AU (each week)

		Category	N	$\hat{\pi}$.	π.	P-value [a] (2-tailed)
Away underdog (week16)	Lose bet	0	32	.37	.50	.018**
	Win bet	1	55	.63		
	Total		87	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

The next analysis is to find inefficiency for the level of closing lines. The reason for this test is that it is probable that betting outcomes would have patterns at each level of closing lines. Three intervals of the closing lines (CL_INT) - 1 for 0 to 5, 2 for 6 to 10, and 3 for over 11- were examined for biases. Table 5.9 shows us that AWAY in 2009 (CL_INT 1) rejected the null hypothesis of a fair bet at the 0.1 level (p = 0.084). Of 109 bets, won 64 bets (WP=0.59), so its predicted probability beat the point spread market in 2009 when the game was expected to be close.

Table 5.9: Away (2009, CL_INT 1)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Away team (2009, CL_INT 1)	Win bet	1	64	.59	.50	.084*
	Lose bet	0	45	.41		
	Total		109	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

AWAY (Table 5.10) rejects the null of the fair net at the highly significant level of 0.01 for the 2008 season (CL_INT 3, p = 0.009).

Table 5.10: Away (2008, CL_INT 3)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Away team (2008, CL_INT 3)	Win bet	1	25	.74	.50	.009***
	Lose bet	0	9	.26		
	Total		34	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

It covered the spreads 25 times out of 34 cases, 0.74 of the WP. The 74% winning percentage could be thought of as very a high probability. From this analysis alone, we cannot know which team, AF or AU, contributed to the AWAY bias. Thus, the HF-AU and the HU-AF categories (CL_INT 3) were tested. The result of AU for the 2008 season is significant at the 0.05 level (p-value = 0.024). Of 29 cases, it only lost 8 bets to HF which is 0.72 of WP. Therefore, this apparent evidence of inefficiency of AU could affect the significant result of the AWAY bias in the same season. Additionally, the AU beat the market (CL_INT 1) for the 2006 season (Table 5.11). It covered the spread by 0.62 of WP at the 0.05 level (p = 0.045). Conversely, the HF beat the spreads more often that the AU in 2005 (CL_INT 1). Therefore, this result might imply that a bias for each CL_INT would randomly occur.

Table 5.11: HF & AU (2005 & 2006, CL_INT 1)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Home favorite (2005, CL_INT 1)	Win bet	1	53	.63	.50	.021**
	Lose bet	0	31	.37		
	Total		84	1.00		
Away underdog (2006, CL_INT 1)	Lose bet	0	31	.38	.50	.045**
	Win bet	1	50	.62		
	Total		81	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

Next, because the HOME-AWAY and the HF-AU categories have biases, it is probable that the FAV-UND (CL_INT 1) also has possible evidence of inefficiency. In fact, there were two significant results in Table 5.12, and both results occurred when the closing lines were below 5.

Table 5.12: Favorite & Underdog (2005 & 2006, CL_INT 1)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Favorite (2005, CL_INT 1)	Win bet	1	85	.63	.50	.004***
	Lose bet	0	51	.38		
	Total		136	1.00		
Underdog (2006, CL_INT = 1)	Lose bet	0	53	.40	.50	.019**
	Win bet	1	81	.60		
	Total		134	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

First, FAV was highly significant in 2005 (p = 0.004, WP = 0.63). Regarding whether HF or AF contributed to the FAV bias, Table 5.11 showed HF beat the market in the same season. Of 84 bets, HF covered the spread as many as 53 times which is 0.63 of WP. It rejected the null of a fair bet at the 0.05 level (p = 0.021). Conversely, AF cannot reject the null hypothesis, although it won 62% of all bets in 2005. Thus, WPs of both teams, HF and

AF, contributed to the FAV bias in 2005. Perhaps there would be a possibility that home field advantage was somewhat underestimated in 2005.

As a follow-up test, the efficiency of each week is tested at each CL_INT. There are two biases detected for the HOME-AWAY category and three biases for the FAV-UND category. In these categories, no bias was still found at CL_INT 2. Table 5.13 shows that HOME's WP is 0.63 in week 4 (CL_INT 1) (p = 0.081), while AWAY in week 9 (CL_INT 3) rejected the null hypothesis at the same significant level.

Table 5.13: Home & Away (CL_INT for each week)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Home team (week4, CL_INT 1)	Win bet	1	35	.63	.50	.081*
	Lose bet	0	21	.38		
	Total		56	1.00		
Away team (week9, CL_INT 3)	Win bet	1	9	.82	.50	.065*
	Lose bet	0	2	.18		
	Total		11	1.00		

a. Based on Z Approximation.
*0.1, **0.05, ***0.01

However, the size of observations was just 11, so it could not be a valid result as evidence of inefficiency. In fact, 18 games are usually played every week, and most of them do not have a large point spread. Thus, most of data set regarding CL_INT 3 would be scarce to satisfy the assumption of a normal distribution and the large sample size. There are actually several significant results found, but the cases are too small.

For the FAV-UND category (Table 5.14), FAV in week 11 (CL_INT 1) rejected the null hypothesis at the 0.1 level (p = 0.072), as it won 38 bets among 61 cases. Also, UND beat the market in week 16 (CL_INT 1) and week 15 (CL_INT 3). The UND bias is highly significant (p = 0.009), as it won as many as 40 bets, and its observed probability is 0.68. It also rejected the null of a fair bet at the 0.1 level in week 15. Based on the above two categories, the HOME-AWAY and the FAV-UND, there might be an existence of possible bias in the same week for the HF-AU or the HU-AF, since the results of all categories are related.

Table 5.14: Favorite & Underdog (CL_INT for each week)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Favorite (week11, CL_INT 1)	Win bet	1	38	.62	.50	.072*
	Lose bet	0	23	.38		
	Total		61	1.00		
Underdog (week16, CL_INT 1)	Win bet	1	40	.68	.50	.009***
	Lose bet	0	19	.32		
	Total		59	1.00		
Underdog (week15, CL_INT 3)	Win bet	1	17	.71	.50	.064*
	Lose bet	0	7	.29		
	Total		24	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

As expected, AU at CL_INT 1(Table 5.15) tended to cover the spread (WP = 0.70, p = 0.014). The result indicates that the skewed result of the AU contributes to a large portion of the UND bias in the same week and CL_INT. Similarly, the AF's statistically significant results contribute to the FAV bias as it won 18 bets which is 0.69 of WP (p = 0.076).

Table 5.15: Away Underdog (week 16, CL_INT 1)

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Away underdog (week16, CL_INT 1)	Lose bet	0	13	.30	.50	.014[a]
	Win bet	1	30	.70		
	Total		43	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

For the last significance test, bets after teams' bye week were tested. Because there were only 16 games each year, all bets after the bye week were combined to test the market inefficiency. The total number of cases was 245, 110 cases for underdog and 135 cases for favorite. As Table 5.16 shows, there was no bias for the HOME-AWAY category. However, FAV bias was found, and it was highly significant ($p = 0.006$). Its WP was 0.62 ($n=135$). This outcome would imply that betting on FAV after its bye week could be profitable. Of FAV, HF could not reject the null of a fair bet ($p = 0.151$), although it won 58% of bets. Conversely, the AF's observed winning percentage was 73%, even though its size of the observations was smaller than the observations for HF's. Also, it is highly significant at the 0.01 level ($p = 0.006$).

Table 5.16: All bets after teams' bye week

		Category	N	$\hat{\pi}.$	$\pi.$	P-value [a] (2-tailed)
Home (bye week)	Win bet	1	74	.54	.50	.444
	Lose bet	0	64	.46		
	Total		138	1.00		
Away (bye week)	Win bet	1	59	.55	.50	.334
	Lose bet	0	48	.45		
	Total		107	1.00		
Underdog (bye week)	Win bet	1	49	.45	.50	.294
	Lose bet	0	61	.55		
	Total		110	1.00		
Favorite (bye week)	Win bet	1	84	.62	.50	.006
	Lose bet	0	51	.38		
	Total		135	1.00		
Home favorite (bye week)	Win bet	1	55	.58	.50	.151
	Lose bet	0	40	.42		
	Total		95	1.00		
Home underdog (bye week)	Win bet	1	19	.44	.50	.542
	Lose bet	0	24	.56		
	Total		43	1.00		
Away favorite (bye week)	Lose bet	0	11	.28	.50	.006
	Win bet	1	29	.73		
	Total		40	1.00		
Away underdog (bye week)	Win bet	1	30	.45	.50	.464
	Lose bet	0	37	.55		
	Total		67	1.00		

a. Based on Z Approximation.

*0.1, **0.05, ***0.01

Possibility of profitable strategies

Based on statistically significant results, the null hypothesis that there are no profitable strategies is tested at the 0.1, 0.05, and 0.01 levels. It is a one tailed test, since we just need to know whether or not the probabilities of winning on bets are statistically higher than 0.5238 on its average. P-values for each case were calculated by hand.

Overall, all possible winning strategies that were revealed in the former section were found to be significantly higher than 0.5238. First, AWAY in week 16 and in 2009 (CL_INT 1) and HOME in week 4 (CL_INT 1) rejected the null of a profitability at the 0.1 level (p-value = 0.085, 0.092, and 0.064 in order). Although, the p-values were higher than the significance test for the null of the fair bet, the differences were not remarkable. Moreover, AWAY at CL_INT 3 was highly significant at the 0.01 level, and its p-value became even lower than the first significance test (0.0059).

Next, for the FAV-UND category, FAV at CL_INT 1 tended to be highly profitable at the 0.01 level for the 2005 season (p = 0.0091), and UND at CL_INT 1 also rejected the null of profitability at the same level (p = 0.0089). Similar to the HOME-AWAY category, there was not much change in each p-value. Moreover, the bye week category showed a smaller p-value of FAV and AF than the first significance test for winning strategies (p = 0.011, 0.005). Therefore, we could say that betting on AF or FAV would have more chances to make positive returns, so if bettors notice this tendency, they could beat the NFL betting market. In fact, 73% of winning for AFs after their bye week is a pretty high percentage in that the bettors can win almost three fourths of the bets. From the significance test for profitability, all winning strategies would be profitable.

CHAPTER 6

DISCUSSION

This thesis tested the EMH in NFL regular seasons from 2002 to 2009. Based on previous literature, it first tried to find some evidence of inefficiency. First of all, similar to previous research, the results of this thesis suggest that it is not easy to find a certain repetitive pattern in the overall market from 2002 to 2009, so the NFL seems to be an efficient betting market as noted by Woodland and Woodland (2000). In addition, it might be impossible for bettors to beat the market, making a positive return, if they wager randomly for a long-term. Thus, bettors would finally expect negative returns on average, even if they consistently bet on the same team or no matter which team they randomly bet. For example, there was no bias for HOME-AWAY category, and this result implies that the sport bookmakers accounted for home advantage or away disadvantage factors like crowd, travel, referee, and familiarity factors noted by Carmicheal and Thomas (2005). In addition, the market makers seem to make a fair and an efficient market although Levitt (2004) found that several bookmakers know the bettors' actions and they set betting lines against people's actions in order to maximize their profits.

However, it was found that some evidence of inefficiency occurred for a certain season or a week and then disappeared as time went by. This result shows that if we see the NFL wagering market more in detail, we might be able to beat the market, but it is also probable that making positive returns is very hard since biases would occur randomly.

Also, unlike dominant findings, UND and HOME bias in previous studies, this thesis confirmed that there was no systematic UND and HOME. In fact, FAV bias and UND bias occurred randomly and AWAY bias usually occurred instead of HOME bias. Thus, the same strategies would not guarantee positive returns to bettors and previous findings are not effective to the data set of this thesis. Also, it implies that even if we find a bias in a season or a week, we might not able to use the same strategy to make positive returns since we would not know which bias would happen next time. In other words, although the bookmakers make intentional biases or unwilled biases, we might be unable to detect biases.

Also, for testing market efficiency late in the season, only AU in week 16 including AWAY and UND showed a bias. The purpose of looking at games late in the season is to see if there is a systematic bias. It might be somewhat harder for the bookmakers to predict future outcomes late in the season since some teams would be already on the playoffs and they might become shirkers in order to prepare for the playoffs. However, week 15 and week 17 that might be thought of as weeks late in the season did not show any evidence of inefficiency. Therefore, a bias in week 16 would not be thought of as a bias caused by above possible reason, so the bookmakers also seem to predict well NFL games late in the season.

Nevertheless, some patterns were found in this thesis. First, all biases for testing each CL_INT occurred at the first and third interval whereas the second interval did not show any evidence of inefficiency. This result might be able to be thought of as little evidence of patterns since betting on a game with small or large closing line gives bettors stronger possibility of making positive returns. The small closing lines might indicate close games, so it might be harder for the bookmakers to predict future outcomes since some external factors would affect the future outcomes such as weather conditions. For the large closing line, it might mean that large FAVs would be shirks since they know they could win the game with certainty although they lose the bet. In fact, the game outcome is the only important thing to players or teams so they do not care about the betting outcomes. Thus, they might not show their performance as usual. Although these reasons would not be reasonable, it is apparent that the larger or the smaller closings, the stronger possibility of a bias in the NFL.

Finally, this thesis found certain biased patterns in games after teams' bye week. FAV was significant and especially AF was highly profitable. This result implies that the bookmakers would miss some information of the effect of bye week on AF performance. In addition, it would be possible that a rest would differently affect team performance and the sport books would underprice AF games after its bye week, ignoring the different effect of the bye week on team performance. Also, one week off in the NFL is a clearer rest period compared to other sports such as NBA, so the bye week bias of this thesis would be more meaningful based on the fact that all NFL teams have the same rest period. Therefore, the bookmakers might need to consider more the effect of the bye week on AF performance when they set the betting lines.

However, this thesis could not prove why FAV and AF performed much better than market expectation after their bye week. Thus, if the same biases would occur in the future, a future study might be able to investigate why these situations happen after teams' bye week.

Another limitation for this study would be that with the data set, it was impossible to prove whether bettors' misperceptions caused biases or whether balancing wagers by the bookmakers unwittingly created evidence of market inefficiency in the NFL. This study just examined the presence of simple betting strategies for wins and profitability. Thus, even if there were simple betting strategies that would be profitable, it was impossible to find which information were missed. To investigate whether there was some information missed, regression models such as the logit model would be appropriate with several independent variables that could be considered by the market makers when they set the lines, game statistics or weather conditions. Also, as mentioned, this thesis did not conduct the binomial logistic regression because of the nature of the data set that possible high correlation between independent dummy variables causes multicollinearity. Thus, with different data set, it would be possible that we could investigate a predicted probability for each team category in the same seasons. Also, the similar examinations of this research are applicable to the NFL O/U wagering market in a future study, so results from the O/U market can be compared with the point spread market.

CHAPTER 7

CONCLUSION

This study investigated the efficient market hypothesis of the NFL wagering market from the 2002 through 2009 seasons. The efficient market hypothesis has usually been applied in traditional financial markets. However, because the sport betting market is a unique prediction market due to a clear ending point and the two markets have several similarities, economists have tested the same hypothesis to see if the market could be thought of as efficient.

The first objective of this study was to test whether several simple betting strategies could reject the null hypothesis of a fair bet and profitability. Betting on the home team, away team, favorite, underdog, home favorite, home underdog, away favorite, and away underdog were all tested. Then the results from this study compared with results from previous studies in the same betting market. Several profitable betting strategies were found. Those strategies occurred somewhat randomly and disappeared quickly. Thus, the same strategies could not be consistently effective. However, away teams including away underdogs and away favorites tended to beat the market and to be profitable, whereas betting strategies of previous studies, betting on home underdogs and large underdogs were not discovered in this study. Therefore, we would not say that the market was highly efficient. For comparison with previous studies, betting on home underdogs and large underdogs were not discovered in this study.

Finally, the bookmakers did not seem to consider or they underestimated the effect of a bye week on the betting lines, especially for the away favorite. After its bye week, it rejected the null of a fair bet and reflected profitability at the highly significant level. Thus, it would be possible for bettors to make abnormal returns by betting on away favorites after the bye week, depending on the amount of wagers. This result is the singular novel finding of this thesis providing evidence of inefficiency in the NFL, and should be tested in other settings to decipher if this is a league-specific or market-specific inefficiency.

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AUTHOR'S BIOGRAPHY

Yoon Tae Sung was born in Seoul, Republic of Korea, on February 28, 1981. He graduated from Yonsei University in 2008 with a Bachelor of Science degree in Sports and Leisure Studies. After finishing his undergraduate studies, he entered the Sport Management Graduate program at the University of Illinois at Urbana-Champaign. Yoon Tae will attend the Florida State University starting the fall to begin his doctoral work in sport management. His research interests are sports economics, economic impact of sports, sports policy and regulation, consumer behavior